Motion Control of Mobile Autonomous Robots Using Non-linear Dynamical Systems Approach

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Abstract. This paper presents a solution to the problem of motion control of an autonomous robot, moving in a dynamical and unstable environment. It is based on non-linear dynamical systems, modelling the state variables that define the motion of a robot under an omnidirectional platform, like its direction of navigation and velocity. The approach used, is based on a set of non-linear differential equations that model the evolution of state variables along time, based on the concept of attractors and repellers. In the official RoboCup Middle Size League field, a target is used to attract the robot to a certain position (could be the ball or a desired position to receive the ball), while a repeller could move the robot away from its original path (given by obstacles in the surrounding environment). The research was firstly carried out in a computational simulation environment and later on with robots in a real environment.

Keywords: Dynamical environments, non-linear dynamical systems, Middle Size League, MSL, RoboCup, mobile autonomous robots, motion control.

1 Introduction

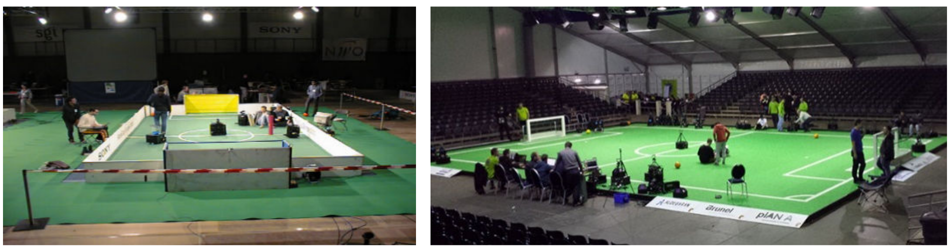
This paper intends to describe a solution for the motion control system of RoboCup's Middle Size League Team, MINHO TEAM, from University of Minho. The proposed method uses world state information gathered by the various on-board sensing systems, to build a meaningful world model, representing the current state of the world the robot is inserted in. Using that information, the robot plans its motion path using non-linear differential equations to model the state variables that define the robot's behavior. Targets act like "attractors" of the system and obstacles act like "repellers", providing a heading, rotational and linear velocities that the robot has to follow. This is performed in order to avoid collisions and meet his target, in an ideal manner. The application of non-linear dynamical systems theories has become more and more important, given the continuous evolution of computational technology. The capability of building powerful control systems that can now be mobile, small, autonomous, and usually act in dynamical environments, creates different and new problems, in comparison to controlled environments. The MSL RoboCup league has been throughout the years, the most evolving and competitive league in RoboCup. As the robots move faster, the existence of highly dynamical environments is inevitable, creating new challenges to the teams. Robots have to cope with the fast-changing dynamical environments and coordinate the motion of every agent on the field. This stimulates great developments in control applications, computer vision, artificial intelligence, cooperative behaviors, always regarding autonomous robots.

Section 2 addresses a general overview over the RoboCup's Middle Size League, while in Section 3 a closer look to the robots motion system is taken, the world modelling approaches and how this relates to the basic intrinsic of the proposed approach. Section 4 describes the mathematical equations, also highlighting the importance and meaning of every variable. Results are presented in Section 5, followed by a discussion. Section 6 presents some conclusions and future work to be performed.

2 RoboCup's Middle Size League

One of the most important leagues in the international RoboCup initiative is the Middle Size League [1], commonly referred to as MSL. It was created in 1997, where MINHO TEAM [2] was a part of it since 1999. Throughout the years, many rule changes have been carried out to increase expectations for the league, coping with the continuous advances in computing technology. This changes forced the teams to evolve, developing new systems and approaches, to both old and new problems, coming up with diverse solutions. The ultimate goal of the RoboCup initiative is to have a team of fully autonomous humanoid robots that will play, and hopefully win, against the winners of the human soccer World Cup, by the year of 2050.

The field of the MSL competition tries to replicate, in a reduced scale, the field of an ordinary human soccer game. In a more basic setup, it uses a green carpet, white line markings and reduced size goals. As the technology of cameras and computers evolve, the processing power and image quality is also visibly better, making very difficult tasks to be performed easier and faster nowadays. The MSL field also increased in size and no longer has the original color markings both on the goals and corners. It is at the moment quite similar to a conventional soccer field but at a scale (Fig. 1).



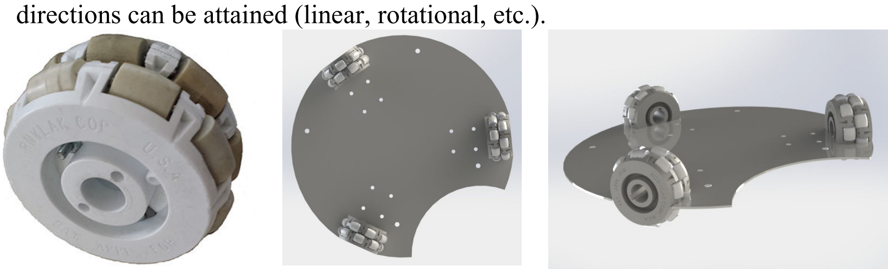
a) b)

Fig. 1. – MSL soccer field: a) previous version with walls and colored markings in the corners and goals; b) actual field with no walls, white goals and no color markings

This evolution is highly related to the public and scientific community demand to see more spectacular games, provided by the MSL Teams and their robots. The rules have little restrictions regarding the development of hardware and software, allowing the teams to be more creative, coming up with new solutions that are shared after the competitions. Next, a typical MSL robot motion system is presented, mainly addressing its omnidirectional nature and the world state modelling mechanisms, which are crucial to the proposed method development.

3 Robotic platform and world modelling

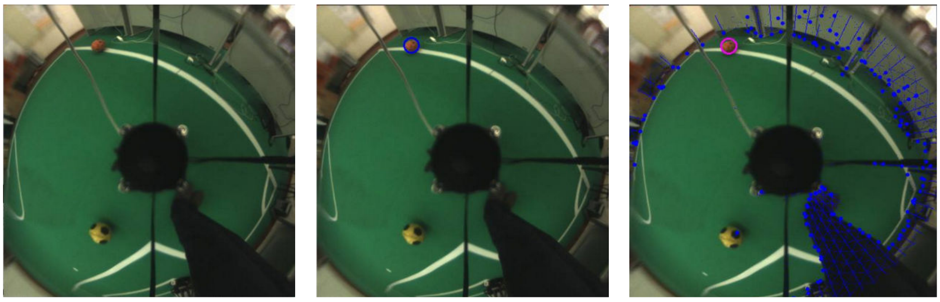
The motion system from every team is almost the same, having little mechanical twists from team to team, having three or four-wheeled systems, but always relying on the omnidirectional [3] capabilities. Having an omnidirectional mobile robotic system is a major improvement from two driving wheel systems, allowing movement in every direction without performing maneuvers. It also allows independent rotational and linear velocities to be achieved. The fact that an omnidirectional platform provides this kind of movements, it allows for faster and direct paths to be made, increasing the dynamical nature of the environment. Robots can actually reach very high motion speeds of up to 4 m/s. The wheels are positioned at the base platform displaced at an angle of 120º from each other as shown in Fig. 2. Special wheels (also known as Swedish wheels) are used, that allow sideway or lateral movement of the wheels. Depending on the speed of each wheel, all sort of platform movements and directions can be attained (linear, rotational, etc.).



a) b) c)

Fig. 2. – Omnidirectional motion: a) Swedish wheel; b) Base platform with three wheels displaced 120º from each other (top view); c) Base platform on the floor.

To gather information of the surrounding environment and build an accurate and efficient world model, the robot uses a Gigabit RGB camera, pointing upwards to a catadioptric mirror [4], thus capturing a “top view” image of 360º around the robot center point (Fig. 3). Using the white field markings captured by the camera, the robot is able to perform self-localization, knowing its global position in the soccer field. It is aided by an Inertial Measurement Unit (IMU), to provide the robot’s true heading. Furthermore, using the vision system, the robot is allowed to know the ball’s position, which is usually a target (an attractor) and the position of obstacles (the repellers), both of human, robotic or static (infrastructure) nature.



a) b) c)

Fig. 3. – Robot's vision using a catadioptric mirror: a) raw image; b) detection of the orange ball (attractor); c) the blue dots are self-detections of obstacle points (repeller).

The capability of self-localization and world modelling [5, 6] is crucial to the proposed method, as the differential equations use this information to model the state variables, defining the desired and optimal motion. As a basic preposition for further developments and explanations of the application, the resultant motion is a combination of the contribution of obstacles, which exerts a repulsive force in the "force field", and the target, which contributes with an attractive force. One can think this through regarding magnetic fields, as the robot being a "north-pole", the target (or targets) being a "south-pole" (which north-poles are attracted to) and the obstacles also as "north-poles", that repel other "north-poles".

Obstacles can be addressed in two different ways: a) by the use of radial scan lines (vision system) as "virtual distance sensors", computing the global obstacle contribution using individual contributions from this "virtual sensors"; b) estimation of the world position of the obstacles, using all the obstacle points gathered, to create the repellers, instead of summing individual contributions. Every pixel in the image is directly mapped to a world distance. In other words, for every pixel in the image, there is a relative value in meters regarding the robot position. With this, after knowing the robot's global positioning, the world and relative positions (in meters) of targets and obstacles can be estimated. Next section addresses the mathematical and theoretical approach taken.

4 Theoretical approach and considerations

Before presenting the theoretical approach and the mathematical equations using non-linear dynamical systems [7, 8, 9], one should be reminded that a global positioning of the robot in the field is calculated. Therefore, the robot's relative position to a target (the ball which is a moving target) and obstacles are accurately obtained, whether by local or shared information. When analyzing a non-linear dynamical system, a linearization process is necessary, at least around the point of operation, to enquire the behavior of the system. It is not enough to fully analyse and model the behavior of more complex non-linear dynamical systems. This linearization process raises two basic limitations:

a) As the linearization consists in an approximation in the neighborhood of a point of operation, it only allows to predict the behavior of the system locally, around that point, not allowing predictions far from the operation point, making a global prediction along time difficult.
b) The dynamics of non-linear systems are much richer and complex than a linear system, existing various phenomena that are direct consequences of the nature of the system, helping to describe and predict the behavior of the system along time. The phenomena are, for example, the existence of bifurcations, that can model behaviors, the existence of various equilibrium points, where the system can converge (be attracted) or diverge (be repelled) from, defining heavily the global behavior of the system, and even chaos.

Regarding the practical application, it is crucial to be able to control and predict the behavior of the robot in every possible situation, even when the environment changes dramatically, being this the base premise to use this approach, instead of others. The existence of equilibrium points is the key, as one can place attracting and repelling equilibrium points (Fig. 4), wherever it is wanted to (global positions in the field or directions/headings), ending up with the desired behavior.

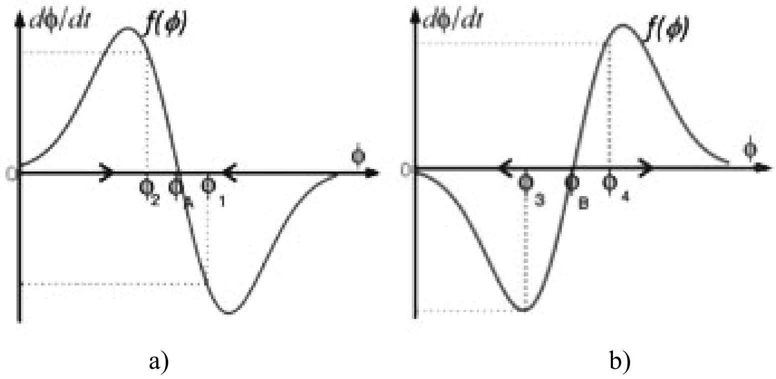


Fig. 4. – Phase plots of dimensional dynamical system: a) An attractor in the direction ϕ_A; b) A repeller in direction ϕ_B (Source: [7], p.11).

Furthermore, it should be stated that the slope of an equilibrium point represents the “force” that a particular attractor or repeller exerts on the system. After explaining the basic concepts that involve the proposed method, clearly the concepts of equilibrium points, attractors, repellers and “force magnitudes”, it should be now stated the theory applied to the practical situation. Every robot should be capable to move smoothly towards its target while avoiding collisions, with one or more obstacles, being robots from the other team or teammates (Fig. 5).

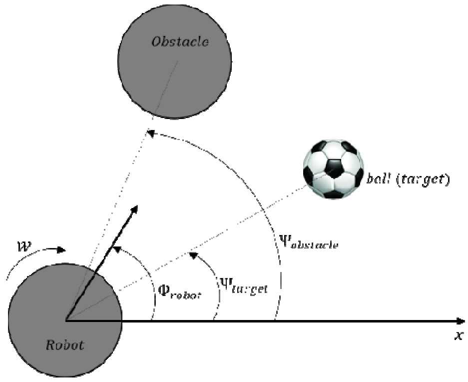


Fig. 5. – Common situation where a robot aims to a target while being disturbed by an obstacle. Different variables/identities can be identified that will take place as world information in the differential equations.

The robot's navigation direction Φ_{robot}, in relation to an external coordinated system is a behavioral variable, representing the direction that the robot should follow along time. Likewise, Ψ_{target} represents the direction of the target from the robot's point of view and $\Psi_{obstacle}$ the direction of an obstacle. This non-linear dynamical systems approach taken here can be divided in two separate subsystems: a) The control of the direction of navigation; b) The control of the robot's velocity.

4.1 Direction of navigation

During every time step in the robot's movement, the behavioral variable Φ_{robot} is updated using differential equation (1).

$$\frac{d\Phi_{robot}}{dt} = f(\Phi_{robot}) = f_{target}(\Phi_{robot}) + f_{obstacle}(\Phi_{robot}) \tag{1}$$

The vector field of equation (1) is built under additive forces, both negative and positive signed, where the evolution of the direction of navigation is a function of forces exerted by the target, f_{target}, which is an attractive force, and a sum of forces exerted by all the existing obstacles, f_{target}, having a repelling nature. When controlling the motion of a robot during a soccer game, the objective is to drive the robot to a certain location, whether to go after the ball or reach a certain position in the field (tactical positioning, both attacking and defensive). The desired location has the direction Ψ_{target}, causing the system to "drive" to that equilibrium point (that direction), being the force it exerts expressed by (2).

$$f_{target}(\Phi_{robot}) = -\lambda_{target} \sin\left(\Phi_{robot} - \Psi_{target}\right) \tag{2}$$

The fixed/equilibrium points of equation (2) are Ψ_{target} and $\Psi_{target} + \pi$, with a magnitude of $-\lambda_{target}$, meaning that the first fixed point will have negative slope, being an attractor, and the other fixed point, right in the opposite direction, that has positive slope, is a repeller, so, f_{target} will only drive the system towards the target if $\lambda_{target} > 0$. The bigger the λ_{target} the faster the robot will go towards the direction of the target. But an upper limit has to be considered, otherwise the repulsive force of the obstacles will be minimal, comparing to the attractive force of the target, and the robot will not avoid obstacles, crashing into them if they step in the path between the robot and the target.

Through the radial scan lines used in the vision system presented in Section 3, a set of 72 distances, spaced by 5º each, make up the real time virtual distance sensors set (Fig. 6).

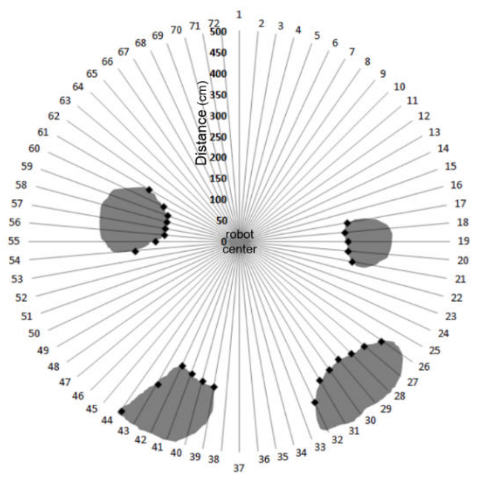


Fig. 6. – Radial scan lines and the resulting set of virtual sensors and world obstacles, relative to the robot center.

The radial scan lines provide the distance to the nearest obstacle, computing then the contribution of each virtual sensor using equation (3).

$$f_{obstacle,i}(\Phi_{robot}) = \lambda_i(\Phi_{robot} - \Psi_i)exp\left[-\frac{(\Phi_{robot}-\Psi_i)^2}{2\sigma_i{}^2}\right] \tag{3}$$

The force exerted by each sensor i is a repulsive force in the Ψ_i direction, where $\Phi_{robot} - \Psi_i$ is a known and constant value, σ_i is the field of view of the sensor, not relating to the external referential whatsoever. The farther the obstacle is, the weaker is its repulsive force, much like a magnet, being a strong repulsive force when the obstacle is detected near the robot. λ_i is the magnitude of the repulsion force, and is given by (4), where β_1 is the maximum force magnitude of the repulsion force, while β_2 is the decay rate of the function, finally, having d_i as the distance measured by the virtual sensor, from the robot to the obstacle:

$$\lambda_i = \beta_1 exp\left[-\frac{d_i}{\beta_2}\right] \tag{4}$$

To obtain the final obstacle contribution, a summation of the individual repulsive forces has to be done, coming up with the total dynamics for the direction of navigation (5).

$$\frac{d\Phi_{robot}}{dt} = \sum_{i=1}^{72} f_{obstacle,i}(\Phi_{robot}) + f_{target}(\Phi_{robot}) \tag{5}$$

The resultant dynamics is then a combination of the obstacle contributions and the target, resulting in a final attractor that changes in time accordingly to the surrounding environment (Fig. 7).

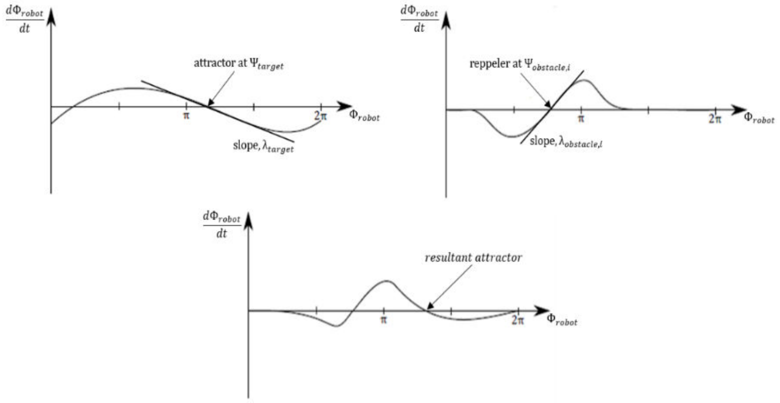


Fig. 7. – Resultant attractor towards the target, combining the forces of attraction from the target and the forces of repulsion from an obstacle (Source: adapted from [7], p.11).

This makes sense because, when the robot is driving towards its goal under the attractive force, should an obstacle come into play, the robot must avoid the obstacle while keeping his track towards the target. When it avoids the target, the repulsive force ceases to exist or it can continue if another moving obstacle shows up, like a defender, always providing the optimal direction of navigation.

4.2 Robot's velocity

When controlling the velocity that the robot is moving, it is highly desirable that a maximum velocity is present to ensure platform stability. It is also desirable to have the robot moving at faster velocities when it is far from the target, and slower when it is near, to avoid hitting the ball when trying to catch it or to stop in the desired position. The hyperbolic tangent function does exactly that, being the velocity modelled by equations (6) and (7):

$$v_{desired}(\mathrm{t}) = -v_{max} \tanh(d_{target}) \tag{6}$$

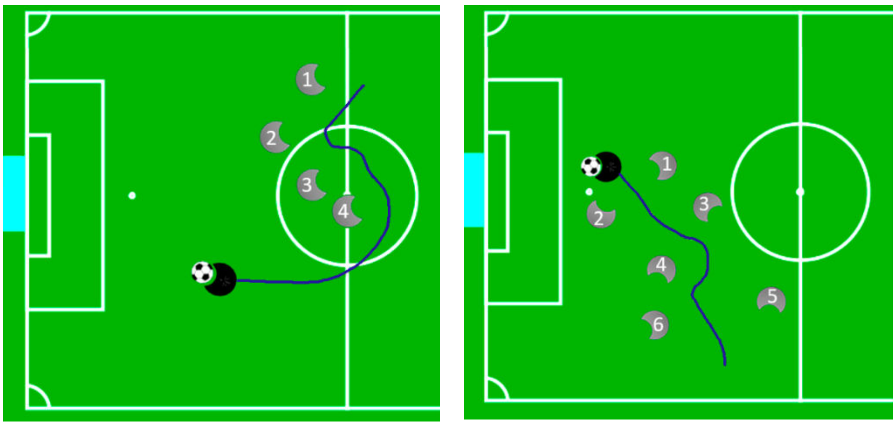
$$\frac{dv}{dt} = \lambda_{velocity}(v - v_{desired}) \tag{7}$$

The desired velocity is computed from the hyperbolic tangent function, given the distance to the target, performing then a calculation of its acceleration. Through Forward Euler numeric integration, the velocity is computed, achieving a smooth trajectory in dynamic environments, always accounting interferences and preventing collisions.

5 Practical application and results

Regarding the highly dynamical environment of a MSL game, using the proposed method has numerous advantages, having also some disadvantages, bringing the necessity to use other supplementary algorithms to build a complete control solution. When it comes to decision making and path planning, this method offers the bifurcations as an inherited property of the non-linear dynamical systems, which models the behavioral variables. The team makes use of other complementary algorithms like the A* algorithm, to help improving the path planning of each robot, using then other complements of path planning in the artificial intelligence layer.

To validate all the prepositions and theoretical results, some tests were carried out using the robots from MINHO TEAM, who comply with all MSL rules, having also the other robots and humans as stationary obstacles, and the ball as a target. A 2D visualization tool was built to aid on the visualization task, in order to debug and help taking some conclusions on the system's performance (Fig. 8). The dark line represents the trajectory of the robot, the black robot is the robot moving with the ball, and the numbered robots the stationary obstacles.



a) b)

Fig. 8. – Two separate conducted tests with the robot moving towards the ball: a) The path chosen was around the obstacles; b) The path chosen was through spaces between obstacles

In the first test (Fig. 8-a) the obstacle 1 has little or no influence to the resulting motion, as it is not blocking the direct path between the robot and the target. Since no obstacle is in the way, the robot follows a straight path towards the target. The robot eventually gets himself near and between obstacles 2 and 3. It then verifies that the gap between them is not enough for it to pass in-between. A repeller is created with the direction in-between the two obstacles, starting to turn around. The system is now under the influence of the obstacles and the target, where the repulsion forces are bigger than the attraction force, due to the proximity of the robot to the obstacles. The target attracts the system towards it (to the right-center), while the repellers push the robot in the opposite direction, forcing it to follow an almost straight line along the position of the obstacles. Once the robot passes by obstacle 4, the target once again becomes the stronger force in the system's force field, turning straight towards the target, reaching the ball's position without colliding with any of the obstacles. The same happens in the second test (Fig. 8-b), where the system is running through an unknown environment, trying to move towards its target, being pushed to other routes given the existence of obstacles, but reaching successfully its target, as it is always trying to meet it in a straight line.

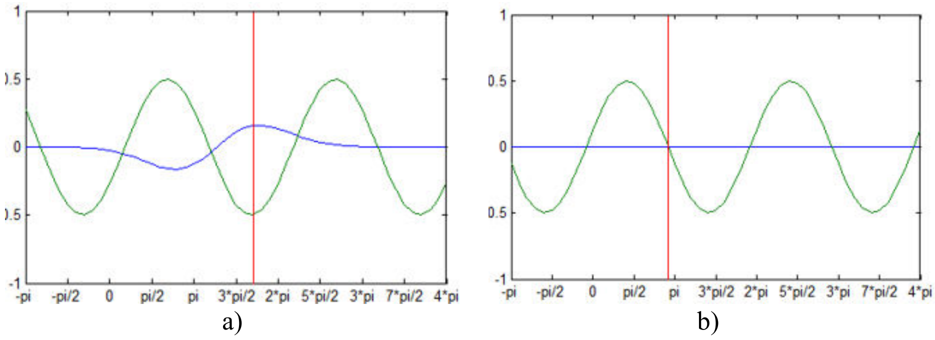


Fig. 9. – Influence of the targets and obstacles on the system: a) the system is under influence of the target and obstacles; b) the system is only under influence of the target.

The direction of the target is near π but, due to the action of the obstacles and the resultant attractor, the system is attracted to another position while influenced by obstacles, making the robot's direction of navigation to be somewhere near $7.\pi/4$. As the robot avoids the obstacles, their influence goes to zero, making the non-linear dynamical system that models the direction of navigation to have an attractor flowing to the target's attractor.

The proposed method has the advantage of allowing a continuous influence in the robot's motion plan, merging the higher level of intelligence with the lower lever control, with an intelligent layer that this method represents. In a higher level, one can plan the path for the robot to reach tactical positioning to receive a pass or drive the ball into a goal scoring position, with artificial intelligence algorithms. But those algorithms alone, cannot forecast the fast movement of obstacles, being expensive, both in performance and processing time, to use them alone. Instead, the presented approach takes on in a local basis, dealing with changes in the closer surrounding environment. It allows the system to accomplish the path defined by the higher level, while taking care of every environment change. It yields a complete smart autonomous system that provides a smooth, fast and trustworthy robot behavior.

During the tests, the robot achieved 80% of its maximum velocity, an encouraging 2.1 m/s, with a processing time under 5 milliseconds, never getting closer than 50 centimeters from the obstacles (predetermined distance). The robot's task becomes more difficult when driving to a certain position while having the ball in its possession, performing rotations (towards the goal) in directions that are not the direction of navigation, making use of the omnidirectional capabilities of the platform. The motion planning is always above the path planning because, should a robot driving the ball towards a goal kick lose the ball, it cannot just keep moving. It has to change his course, retrieve the ball, changing its target, and re-target the goal scoring position, overriding the path planning directives.

6 Conclusion

This paper has made a theoretical and practical analysis to the motion control method, based on behavioral variables modelled by non-linear dynamical systems, applied to the robots and requirements of RoboCup's Middle Size League. The presented method is not sufficient alone. It does not provide a higher level (global) intelligent path planning. It only allows a very efficient and smooth motion (local) planning, when the necessity of avoiding dynamic obstacles or pursuing a moving target comes into place. It will be perfectly integrated with the higher level path planning algorithms, producing an intelligent, efficient and accurate motion and path planning system. Using the attractor-repeller mechanism, it is allowed to strategically place both attractors and repellers in the system. This produces a high impact in the robot's behavior, modelling its motion path at all time steps, accurately, faster and yielding smooth motion even at velocities up to 2 m/s. The results obtained met the expectations once the robot successfully reached its targets, driving the ball to kicking positions, while avoiding obstacles.

As for further work, various high level path planning algorithms shall be tested and implemented, compared with each other, trying to achieve the best cooperation possible between the higher, middle and lower layers of the motion control system. This will promote the creation of a hybrid system, which is more efficient and robust than any of the layers alone, creating a control system that is good enough to control a team of robots able to play a RoboCup's Middle Size League game.

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